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Enhanced Inception Residual CNN for Lung Nodule Detection Using LIDC Dataset

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Abstract: Over Several Decades the early identification of lung nodules in computed tomography images is avitalstage in the diagnosis and assessment of lung cancer. The variation in nodule size, shape, texture, and intensity makes automated detection a challenging image-analysis task. In our work an Enhanced Inception Residual Convolutional Neural Network for detecting pulmonary nodules from the Lung Image Database Consortium and Image Database Resource Initiative dataset. The proposed network combines the multi-scale feature learning capability of Inception modules with residual connections, allowing the model to capture both local and broader image characteristics while maintaining effective information flow through the deeper layers. The overall framework includes image pre-processing, augmentation, feature learning, and classification to separate nodule regions from non-nodule regions. Augmentation is incorporated to provide greater variation in the training samples and improve the ability of the network to perform on previously unseen images respectively. The effectiveness of the proposed approach is assessed using accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve. In order to examine the contribution of the enhanced architecture, The performance is compared with conventional convolutional neural network, residual convolutional neural network, and Inception convolutional neural network models. The study aims to develop a dependable computer-aided detection method that can learn relevant characteristics of pulmonary nodules and provide consistent support for computed tomography image interpretation respectively.

Keywords: Lung nodule detection, lung cancer, convolutional neural network, Inception architecture, residual learning, medical image analysis, computed tomography, computer-aided detection, image classification, feature extraction, pulmonary nodule.

I. INTRODUCTION

Lung cancer remains a major health concern, and early identification of pulmonary nodules from computed tomography images can support timely diagnosis. However, differences in nodule size, shape, texture, and intensity make automatic detection difficult. The LIDC-IDRI dataset has provided a widely used annotated resource for developing and evaluating computer-aided lung nodule detection methods [1]. The research work was explored conventional CNNs, residual networks, multi-scale learning, attention mechanisms, segmentation models, and hybrid approaches respectively [2] [15]. Although these methods have shown promising performance, a single architecture may not effectively capture both fine nodule details and broader image patterns while maintaining efficient information flow through deeper layers. To address this gap, the study proposes an Enhanced Inception Residual Convolutional Neural Network for lung nodule detection. The proposed model combines Inception-based multi-scale feature extraction with residual learning to improve feature representation and information propagation. The model is evaluated using accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve respectively.

II. LITERATURE REVIEW

The development of automated lung nodule detection has been supported by the availability of well-annotated computed tomography datasets. The LIDC-IDRI database was introduced as a public reference dataset containing CT scans and expert annotations of lung nodules, providing an important foundation for computer-aided detection research [1]. The researcher evaluated different computer-aided detection systems using the LIDC-IDRI database and highlighted the importance of reliable automated nodule identification in CT images [2]. The growth of deep learning, convolutional neural networks were applied to automatically detect pulmonary nodules and reduce the effort required for examining large CT volumes [3]. CNN-based approaches were also developed for automatic feature extraction and nodule classification, demonstrating the usefulness of deep feature learning for this task [4]. Hybrid deep-learning methods combined optimization, segmentation, feature selection, and

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classification to improve the overall detection process [5]. In this model they focused on lung segmentation and nodule type identification, showing that accurate segmentation can support subsequent nodule analysis [6]. Multi-scale deep-learning methods using dilated convolution and ensemble classification were investigated to capture nodule characteristics at different spatial levels [7]. Optimization-based deep convolutional networks were further explored to improve segmentation, parameter selection, and nodule detection [8]. The above research has concentrated on developing more advanced architectures for detecting small and visually complex nodules. Deep-learning models have been proposed for early nodule detection by automatically learning relevant patterns from CT images [9]. Hybrid approaches combining optimized clustering, residual networks, statistical features, and recurrent learning have also been explored for improved segmentation and classification [10]. U-Net-based segmentation combined with CNN classification has been studied along with comparisons against established architectures such as Efficient Net, VGG, and Inception [11]. Three-dimensional ensemble networks have further demonstrated the benefit of combining complementary deep-learning models for pulmonary nodule classification [12]. U-Net with neural architecture search has also been investigated to improve the design of models for lung cancer detection and classification [13]. Attention and weight-excitation mechanisms have been incorporated into U-Net architectures to focus on important nodule regions and improve segmentation quality [14]. The additional value of deep-learning-based automated analysis has also been examined in lung nodule detection applications [15]. Although these studies have achieved promising results, challenges remain in simultaneously capturing fine local details and broader contextual information while maintaining effective feature propagation through deeper networks. To address this limitation, the proposed Enhanced Inception Residual Convolutional Neural Network combines Inception modules with residual connections. The Inception component enables multi-scale feature extraction by processing image information at different receptive-field sizes, while the residual connections facilitate information flow and help preserve useful features across deeper layers. The combination is intended to provide a more effective representation of pulmonary nodules with different sizes, shapes, and textures, thereby improving the reliability of automated lung nodule detection using the LIDC-IDRI dataset respectively.

III. PROBLEM STATEMENT

The research involves with several preliminary assessments and challenges involved in

1. **High variability of pulmonary nodules:** Variations in the size, shape, texture, and intensity of pulmonary nodules make their accurate identification in computed tomography images challenging.
2. **Difficulty in detecting small nodules:** Small and low-contrast nodules may have similar characteristics to surrounding lung tissues, which can lead to missed or incorrect detections.
3. **Insufficient multi-scale feature representation:** Conventional convolutional neural network models may not effectively capture both fine-grained and broader contextual features required for detecting nodules of different sizes.
4. **Feature degradation in deeper networks:** Increasing network depth can make effective information propagation difficult, limiting the ability of the model to preserve and learn relevant nodule features.
5. **Requirement for a robust detection framework:** These challenges highlight the need for an improved architecture that integrates multi-scale feature extraction andresidual learning to achieve more reliable and accurate lung nodule detection from CT images.

IV. PROPOSED FRAMEWORK

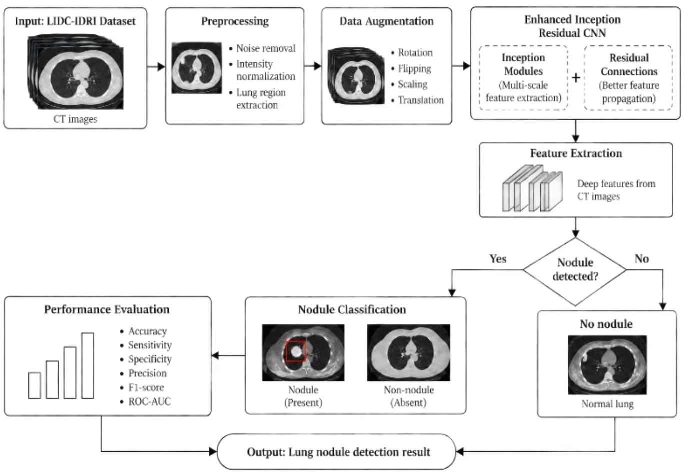

Figure 1: Proposed Enhanced Inception Residual CNN for Lung Nodule Detection

The above figure presents the proposed lung nodule detection framework using the LIDC dataset. The CT images were pre-processed and augmenting before transferred to the Enhanced Inception Residual CNN. Inception modules extract multi-scale features, while residual connections improve feature propagation. The extracted features are then used to classify images as nodule-present or non-nodule respectively.

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Steps involved in this approach

Enhanced Inception Residual CNN

Input: LIDC Dataset X
Output: Nodule Prediction $\hat{Y}$

$X_p \leftarrow$ **preprocess (X)**

$X_n \leftarrow$ **noise removal** (X_p)

$X_i \leftarrow$ **intensity normalization** (X_n)

$X_l \leftarrow$ **lung region extraction** (X_i)

$x_a \leftarrow$ **data augmentation** (x_l)

$f_0 \leftarrow x_a$

$f_1 \leftarrow conv_{1}\times_{1}(f_0)$

$f_2 \leftarrow conv_{3}\times_{3}(f_0)$

$f_3 \leftarrow conv_{5}\times_{5}(f_0)$

$f_4 \leftarrow pool(f_0)$

$f^{I} \leftarrow concatenate(f_1,f_2,f_3,f_4)$

$f^{R} \leftarrow f^{I} + f_0$

$f \leftarrow convolution(f^{R})$

$z \leftarrow$ **global average pooling** (f)

$p \leftarrow 1/(1 + e^{-}(wz+b))$

if $p \geq 0.5$ **then** $\hat{y} \leftarrow 1$ **else** $\hat{y} \leftarrow 0$ **end if**

Performance evaluation

return $\hat{y}$

end

V. RESULTS AND DISCUSSIONS

Table 1: Accuracy for the Enhanced Inception Residual CNN in LIDC DATASET images

No. of Images	Accuracy (%)
100	96.23
200	96.15
300	96.25
400	97.12
500	97.82

The above table represents the Accuracy achieved by the Enhanced Inception Residual CNN for different numbers of input images respectively.

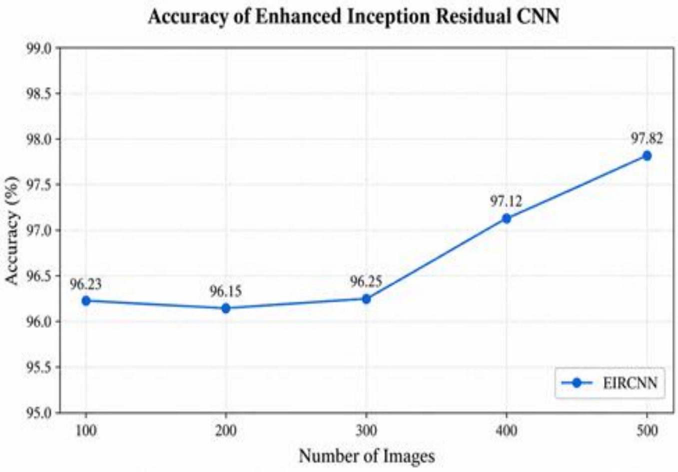

Figure 2: Accuracy for Enhanced Inception Residual CNN in LIDC DATASET images

The above graph illustrates the Accuracy trend of the proposed model across the selected image counts. The increasing trend indicates consistent improvement in nodule classification performance with more input images respectively.

Table 2: Precision for the Enhanced Inception Residual CNN in LIDC DATASET images

No. of Images	Precision (%)
100	83.04
200	83.30
300	83.81

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No. of Images	Precision (%)
400	84.25
500	84.87

The above table represents the Precision achieved by the Enhanced Inception Residual CNN for different numbers of input images respectively.

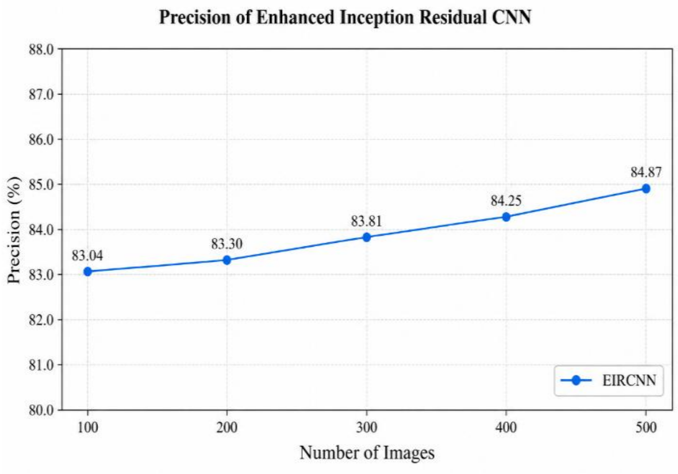

Figure 3: Precision for Enhanced Inception Residual CNN in LIDC DATASET images

The above graph illustrates the precision trend of EIRCNN across different numbers of input images respectively.

Table 3: Recall for the Enhanced Inception Residual CNN in LIDC DATASET images

No. of Images	Recall (%)
100	97.10
200	97.17
300	97.43
400	97.82
500	97.96

The above table represents the Recall achieved by the Enhanced Inception Residual CNN for different numbers of input images respectively.

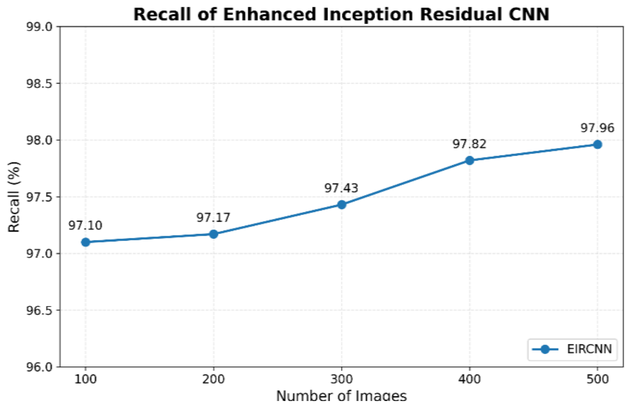

Figure 4: Recall for Enhanced Inception Residual CNN in LIDC DATASET images

The above graph illustrates the Recall trend of EIRCNN across different numbers of input images respectively.

Table 4: F-Measure for the Enhanced Inception Residual CNN in LIDC DATASET images

No. of Images	F-Measure (%)
100	92.11
200	92.16
300	92.48
400	92.88
500	92.91

The above table represents the F-Measure achieved by the Enhanced Inception Residual CNN for different numbers of input images respectively.

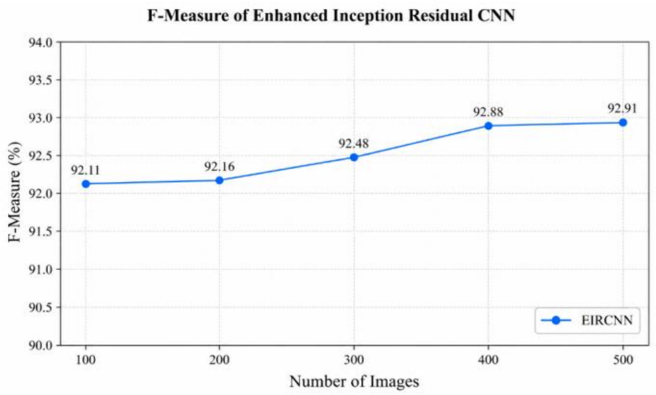

Figure 5: F-Measure for Enhanced Inception Residual CNN in LIDC DATASET images

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The above graph illustrates the F-Measure trend of EIRCNN across different numbers of input images respectively.

The above performance of the proposed Enhanced Inception Residual CNN was evaluated using different numbers of LIDC dataset images, ranging from 100 to 500. The accuracy increased from **96.23% to 97.82%,** showing improved overall classification performance with more input images. Precision also improved steadily from **83.04% to 84.87%,** indicating better identification of nodule-positive images. Recall increased from **97.10% to 97.96%,** demonstrating the model's ability to detect a higher proportion of actual nodules. Similarly, the F-Measure improved from **92.11% to 92.91%,** reflecting a better balance between precision and recall. Therefore, the results indicate the increasing number of input images supports more consistent and effective lung nodule detection using the proposed model respectively.

VI. CONCLUSION

The proposed Enhanced Inception Residual Convolutional Neural Network demonstrated effective performance for lung nodule detection using images from the LIDC dataset. The results show that increasing the number of input images improves accuracy, precision, recall, and F-Measure, indicating reliable feature learning and classification capability. The combination of multi-scale Inception features and residual connections helps the model capture important nodule characteristics while maintaining effective information flow. However, further improvement is required to enhance detection of small and difficult-to-identify nodules. As future work, an **Enhanced Pre-Activation Residual Convolutional Neural Network** will be investigated to improve feature propagation and representation learning for more accurate lung nodule detection respectively. The future model can also be evaluated on larger and independent CT datasets to assess its robustness and generalization capability.

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